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Multi Resolution features of Content Based Image Retrieval

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***Abstract*—Many content based retrieval systems have been proposed to manage and retrieve images on the basis of their content. In this paper we proposed Color Histogram, Discrete Wavelet Transform and Complex Wavelet Transform techniques for efficient image retrieval from huge database. Color Histogram technique is based on exact matching of histogram of query image and database. Discrete Wavelet transform technique retrieves images based on computation of wavelet coefficients of subbands. Complex Wavelet Transform technique includes computation of real and imaginary part to extract the details from texture. The proposed method is tested on COREL1000 database and retrieval results have demonstrated a significant improvement in precision and recall.**

***Index Terms*— Content Based Image Retrieval, Color Histogram, Discrete Wavelet transform, Complex Wavelet Transform, Texture, Precision, Recall.**

I. Introduction

Due to availability of large multimedia database, Digital libraries and advancement in Information Technology it is possible to share the visual information worldwide through global computer network, World Wide Web (www). This large database created by educational, medical, industrial and scientific applications requires efficient and automatic procedure for indexing and retrieving the images from database[1].

Generally two methods are used to retrieve the images from database: context based approach and content based approach. In context based approach images are annotated manually and then retrieved using context retrieval technique. This manual annotation is time consuming and expensive for large image database. So it is very difficult to retrieve variety of images from the database. To avoid this difficulty Content based image retrieval (CBIR) technique is adopted. This technique uses various image features like color, shape, texture to search the desired images from huge database, which finds its application in medicine, education, entertainment, research and crime detection [2,3].There are various approaches and methods for content based image retrieval. One of the simplest and easiest method is color histogram, which is based on visual features of image like color, shape and texture [4].

CBIR system focuses on retrieving images from the database; the system depends on the way the indexing is being implemented. The way or method in which an image is stored will affect how it will be retrieved later. This work aim is to develop an indexing algorithm based on existing CBIR studies, which can save more storage space and improve the retrieval process.

Contents of query image are extracted during run time and used to match against the available huge database. The result of the query is a set of images having same features as that of the query [5].

Most of the CBIR systems rely on various distances, similarity or subjective resemblance to some extent. The Euclidean distance, the Manhattan distance, the Minkowski-form distance and quadratic form distance are some of the most commonly used functions to describe the similarities between images [6, 7].

The direction dependent Gabor filter is also used to extract the image features for image retrieval. The accuracy of filter depends on the angle chosen. To get rid of from angle dependency Radial basis function Gabor filer is used [8].

In this paper we propose three methods of CBIR viz. Section II gives idea about CBIR using Color Histogram, Section III gives idea about CBIR using Discrete Wavelet Transform and Section IV explain about CBIR using Complex Wavelet Transform. Section V shows results of CBIR using above methods. And results are compared using suitable measures like Precision and Recall. We finally conclude in Section VI.

II. CBIR Using Color Histogram

Color is most intuitive feature of an image and to describe colors generally histograms are adopted. Histogram methods have the advantages of speediness, low demand of memory space. For categorizing images, color features can provide powerful information and they are used for image retrieval. In color histogram each pixel is associated with specific histogram bin on the basis of own color and not on the basis of color similarities across different bins or dissimilarities in the same bin are not considered. Every pixel is explained by three components of color space. Red, Green and Blue are the components in RGB color space.

The color histogram is prepared by computing the pixels of each color. The different color axes are divided into bins. When indexing the image, the color of each pixel is found and corresponding bin's count is incremented by one[9].

Color histogram is the probability mass function of the

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image intensities. Color histogram is given by:

$$H_{A,B,C}(a,b,c) = N.\ \mathrm{Prob}(A=a, B=b, C=c) \quad (1)$$

where A, B and C are the three color channels (R,G,B or H,S,V) and N is the number of pixels of the image .There are several distance measures are available to determine the similarities of color histogram.

In this work we calculate histogram Euclidean distance. If m and n are two color histograms, then Euclidean distance between histogram m and n is given as

$$d^2(m,n) = \sum_A \sum_B \sum_C (m(a,b,c) - n(a,b,c))^2 \quad (2)$$

The minimum distance between bins signifies exact match with query image. We have used COREL database of 1000 images for evaluation of algorithms. Figure 4 shows query image and retrieved images. Figure 5 shows histogram of query image and retrieved images.

III. DISCRETE WAVELET TRANSFORM IN CBIR

Wavelet is a mathematical tool that can decompose a temporal signal into a summation of time–domain basis function of various frequency resolutions. Wavelet can serve as deterministic or non-deterministic basis for generation and analysis of natural signals to provide better time-frequency representation, which is impossible with Fourier analysis. Wavelet is a powerful tool for representing nonlinearity [10]. The continuous one dimensional wavelet transform is a decomposition of $f(x)$ can be represented by the superstition of daughters $\psi_{a,b}(x)$ of a mother wavelet $\psi(x)$. Where $\psi_{a,b}(x)$ can be given as:

$$\psi_{a,b}(x) = \frac{1}{\sqrt{a}}\psi\left(\frac{x-b}{a}\right) \quad (3)$$

Where 'a' is the scaling or dilation parameter and 'b' is the time shift or translation parameter.The continuous wavelet transform of $f(x)$ is defined as

$$W(a,b) = \int_{-\infty}^{\infty} f(x)\psi^*_{a,b}(x)dx \quad (4)$$

Function $f(x)$ can be restored by inverse wavelet transform, which is given as:

$$f(x) = \frac{1}{C}\int_{a=-\infty}^{\infty}\int_{b=-\infty}^{\infty}\frac{1}{|a^2|}W(a,b)\psi_{a,b}(x)da.db \quad (5)$$

Continuous wavelet transform maps a one dimensional function $f(x)$ to a function $W(a,b)$ of two continuous real variables 'a' and 'b' which are the wavelet dilation and translation respectively.

Consider a non redundant wavelet representation

$$f(x) = \sum_{k=-\infty}^{\infty}\sum_{l=-\infty}^{\infty} d(k,l)2^{-k/2}\psi(2^{-k}x - l) \quad (6)$$

If we compare equation 5 and equation 6, it is observed that equation 6 replaces discrete values for 'a' and 'b', here a = 2^k where k is an integer. At any dilation i.e. 'a' the translation parameter takes the value of the form $2^k l$ where l is an integer. The value $d(k,l)$ are related to values of the wavelet transform at a = 2^k and b = $2^k l$. This corresponds to sampling of the coordinates (a, b), such a process is called as dynamic sampling because consecutive values of the discrete scales as well as the corresponding sampling intervals differ by a factor of two. The two dimensional sequence $d(k,l)$ is known as discrete wavelet transform (DWT) of $f(x)$. 2D version of wavelet can be implemented by means of applying 1D wavelet transform across row and column of image independently.

The discrete wavelet transform can be used to analyze, or decompose, signals and images. This process is called decomposition or analysis and how those components can be assembled back into the original signal without loss of information. This process is called reconstruction, or synthesis. Analysis filter bank block decomposes a broadband signal into a collection of subbands with smaller bandwidths and slower sample rates. The block uses a series of high pass and low pass filters to repeatedly divide the input frequency range. Figure 1 shows three level filter bank.

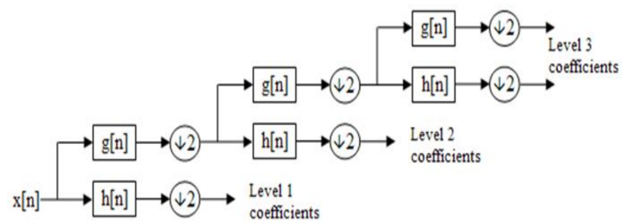

Figure 1 Three level Filter Bank

In the DWT generated hierarchical subband structure, a coefficient at any subband and at any level (except for the lowest level, i.e. level number 1) can be related to a set of coefficients at the lower levels at corresponding subbands. A coefficient at a higher level is called the Parent of all the corresponding coefficients at the same spatial orientation at lower level, which is known as its children.

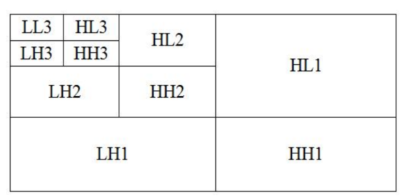

Figure 2 Three level DWT

Figure 2 shows three level hierarchy in DWT. The scanning of coefficients starts from parents to child. For three level transform scanning start from LL_3 followed by HL_3, LH_3, HH_3 followed by the subband at lower level i.e. HL_2, LH_2, HH_2 followed by next lower level i.e. HL_1, LH_1, HH_1. Such a scanning pattern ensures maximum exploitation of the inter-subband correlation [11].

We have used COREL database for evaluation of algorithm and Euclidean distance as a measure. Figure 6 shows query and retrieved images using DWT. Figure 7 shows wavelet energy diagram. Figure 8 shows coefficients of subbands.

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IV. Complex Wavelet Transform in CBIR

Wavelet techniques are used to remove noise from signal/image, for classification of data and for data compression means wavelet can be used to perform various operations in image and signal processing. But wavelet technique has certain disadvantages:

If there is shifting in time for input signal then there is unpredictable changes in values of transform coefficients. Due to this shifting DWT coefficients cannot discriminate between input signal shifts [12].

Images contain various edges with various type of orientations and DWT can support only horizontal, diagonal and vertical orientations. So wavelet has poor directionality.

Major drawback of DWT is that it consider only real coefficient filters associated with real wavelets gives only real valued approximations but we can use complex signals for various operations in image processing and phase of complex signal is calculated by its real and imaginary coefficients. Here DWT fails to provide accurate phase information. This disadvantage can be overcome by using Complex valued filtering [13, 14, 15].

Fourier transform is complex valued oscillating sinusoids given by:

$$e^{j\Omega t} = \cos(\Omega t) + j\sin(\Omega t) \qquad (7)$$

Where $j = \sqrt{-1}$. The oscillating components form Hilbert transform pair [16].

So Complex Wavelet Transform with complex valued scaling function and complex valued wavelet is given as

$$\psi(x) = \psi_r(x) + j\psi_i(x) \qquad (8)$$

Where $\psi_r(x)$ and $\psi_i(x)$ form Hilbert transform pair, so $\psi(x)$ is the analytic signal. Same concept is applied in the design of filter banks of DWT to produce Complex Wavelet Transform.

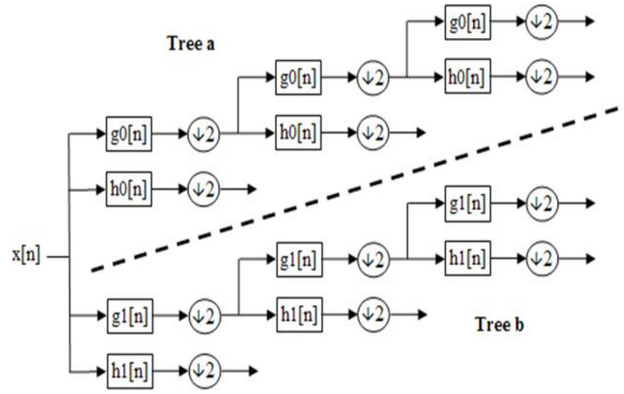

Figure 3 Filter bank of DT-Complex Wavelet Transform

There are two types of Complex Wavelet Transform namely Redundant Complex Wavelet Transform (RCWT) and Non-redundant Complex Wavelet Transform (NRCWT).

The RCWT includes two similar Complex Wavelet Transforms namely Dual tree DWT based Complex Wavelet Transform (DT-CWT) and Selesnick’s DT-Complex Wavelet Transform. These transform contains two filter banks trees working in parallel with respective filters of both the trees. Structure of both filter bank is same but design procedure to generate filter coefficient is different. Figure 3 shows filter bank of DT-Complex Wavelet Transform.

Figure 9 shows query image and retrieved images using CWT. Figure 10 shows energy diagram and Figure 11 shows complex coefficients.

V. Result And Discussion

The performance or evaluation of the image retrieval algorithm is measured by Precision and Recall curve [17,18].

$$Precision = \frac{Number\ of\ relavent\ Images\ Retrieved}{Total\ Number\ of\ Images\ Retrieved} \qquad (9)$$

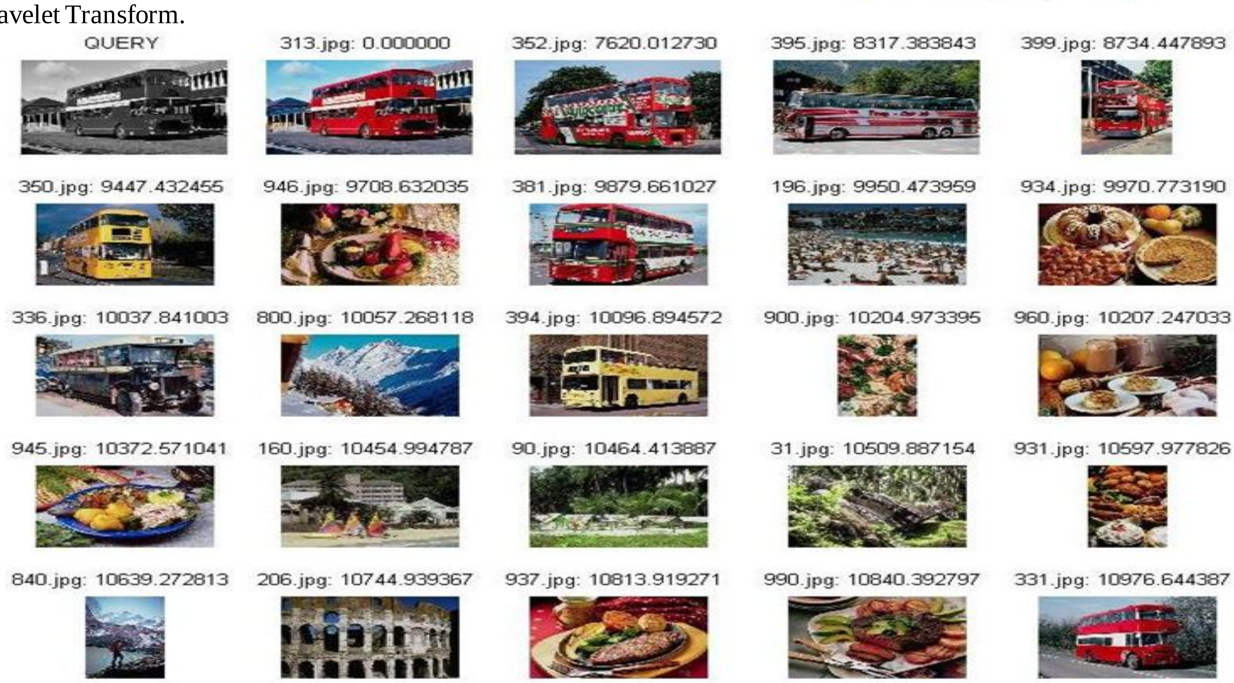

Figure 4 Query Image and retrieved images using Color Histogram

$$Recall = \frac{Number\ of\ Relavant\ Images\ Retrieved}{Total\ Number\ of\ Relavant\ Images} \quad (10)$$

We have computed precision – recall values for queries. Figure 12 shows precision and recall curve for above three techniques.

VI. Conclusion

In this paper, a comparative study has been carried out on feature extraction using Color Histogram, Discrete Wavelet Transform and Complex Wavelet Transform techniques. We have taken Euclidean distance as a measures for retrieving the similar images from the data base. From this experiment we conclude that Color Histogram technique is based on matching of histogram of query image and retrieved images and gives result based on exact match. Discrete Wavelet Transform technique computes detailed coefficients in terms of subbands of query image and retrieved images. So this technique gives detailed information than Color Histogram. Complex Wavelet Transform extracts information from both real and imaginary part. So we can say that Complex Wavelet Transform retrieval algorithm extracts maximum information from the database as compared to previous techniques.

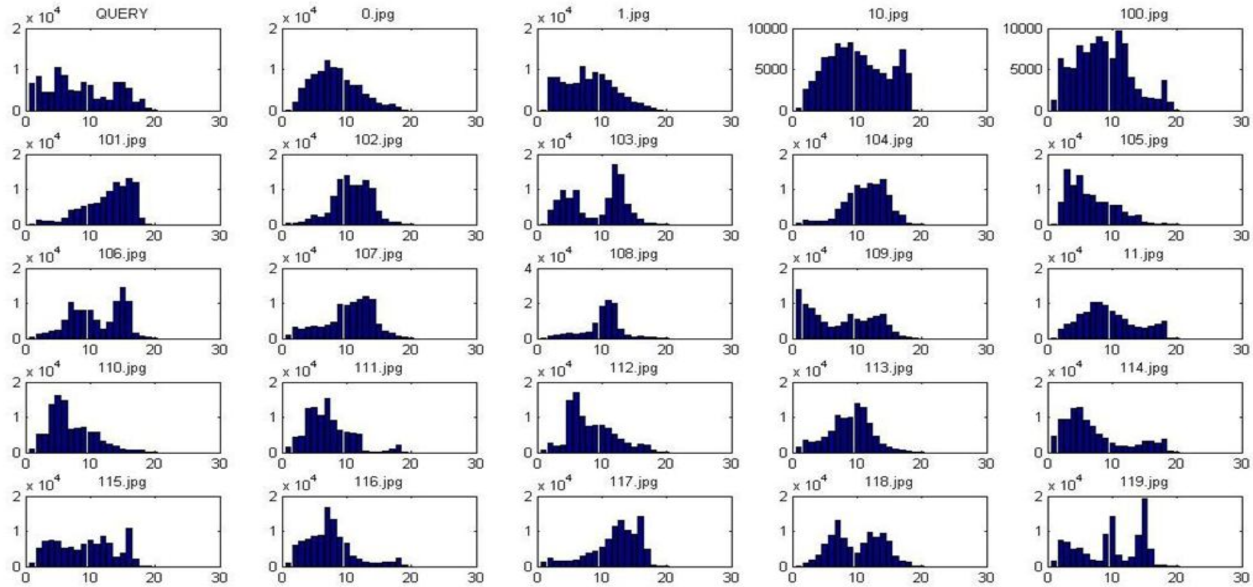

Figure 5 Histogram of query and retrieved images

Figure 6 Query image and retrieved images using Discrete Wavelet Transform

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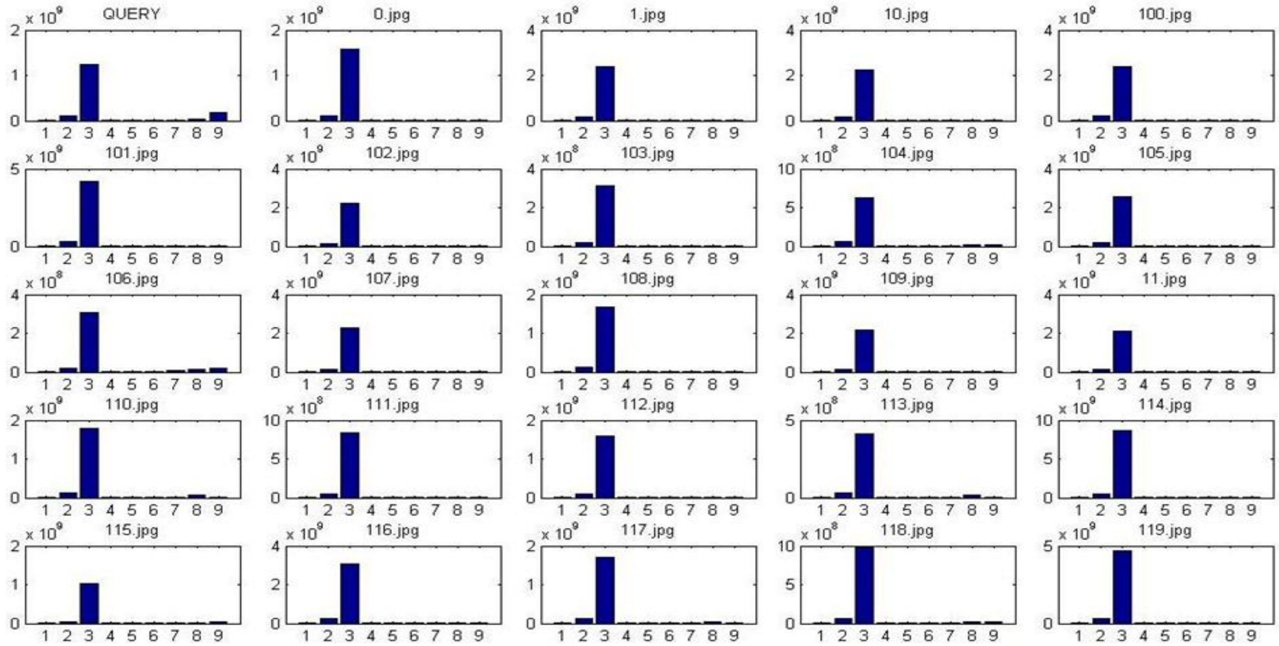

Figure 7 Wavelet Energy Diagram

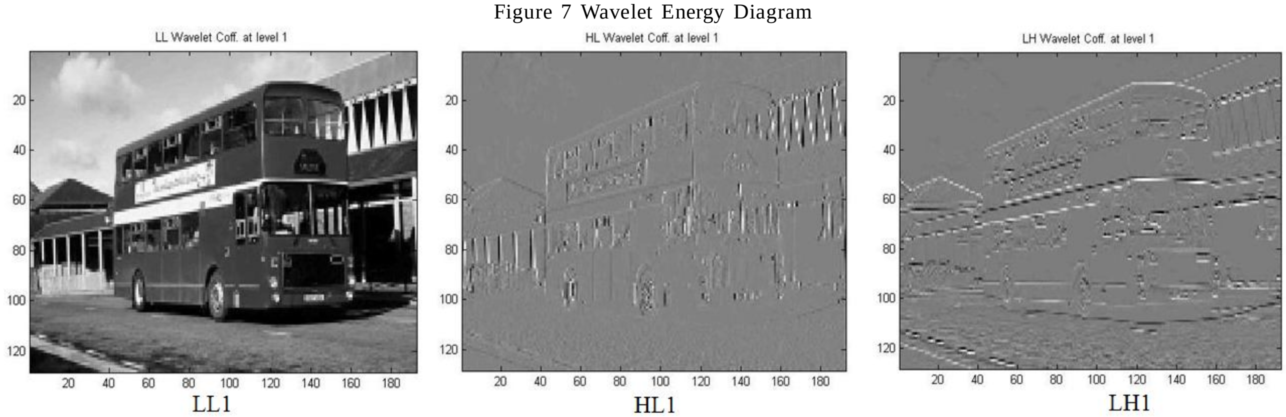

Figure 8 Coefficients of Subbands

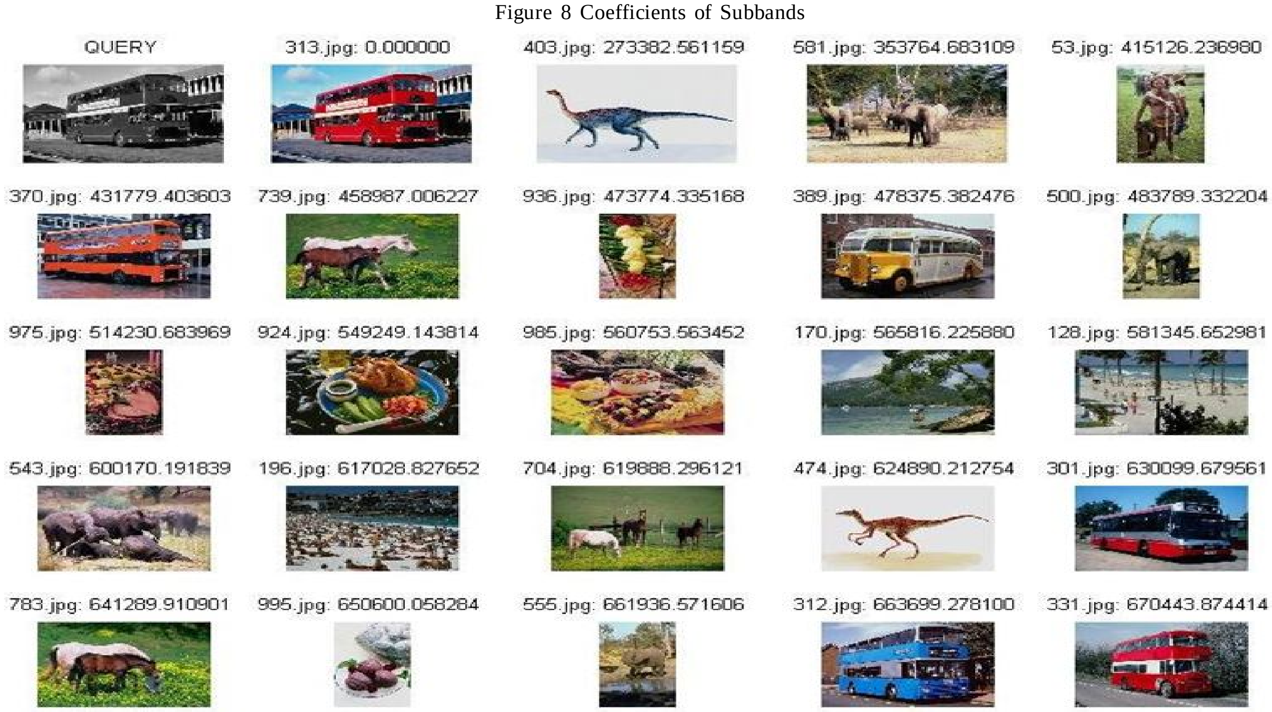

Figure 9 Query and retrieved Images using Complex Wavelet Transform

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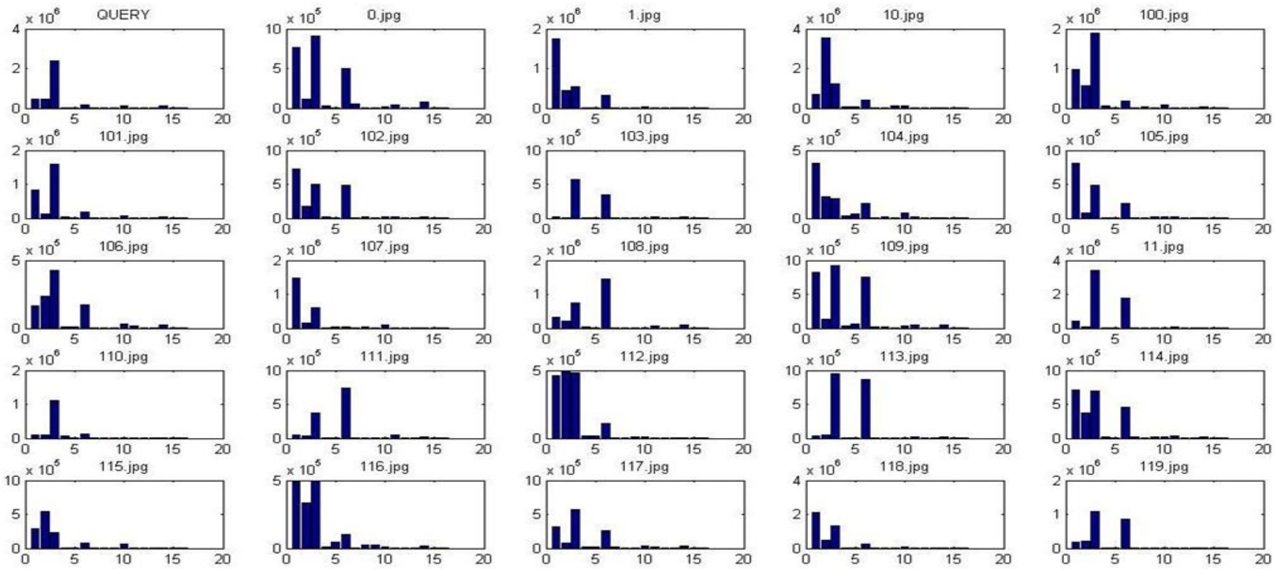

Figure 10 Complex Wavelet Transform Energy Diagram

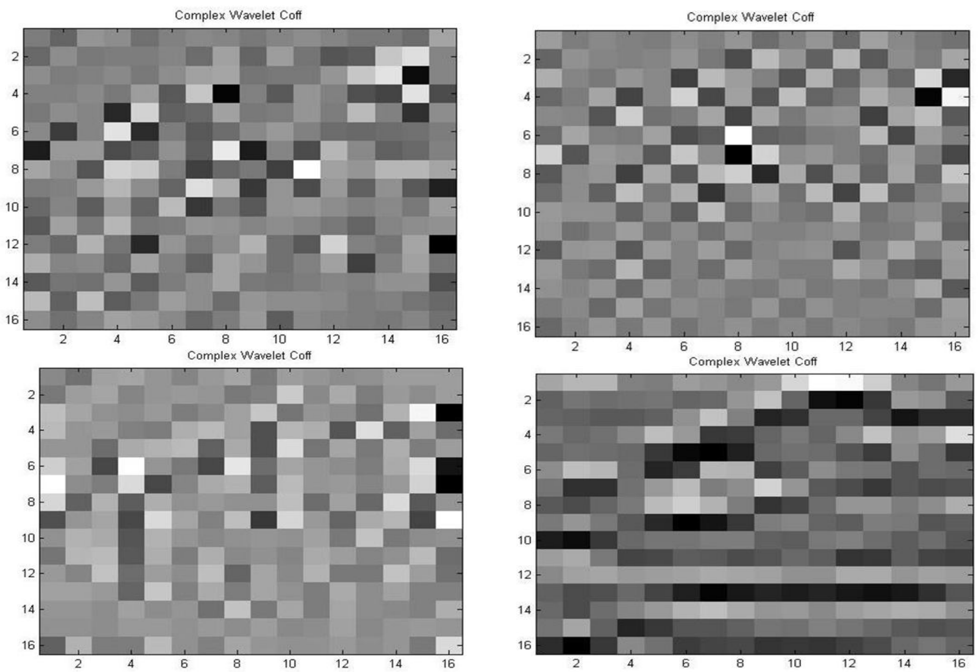

Figure 11 Complex Wavelet Coefficients

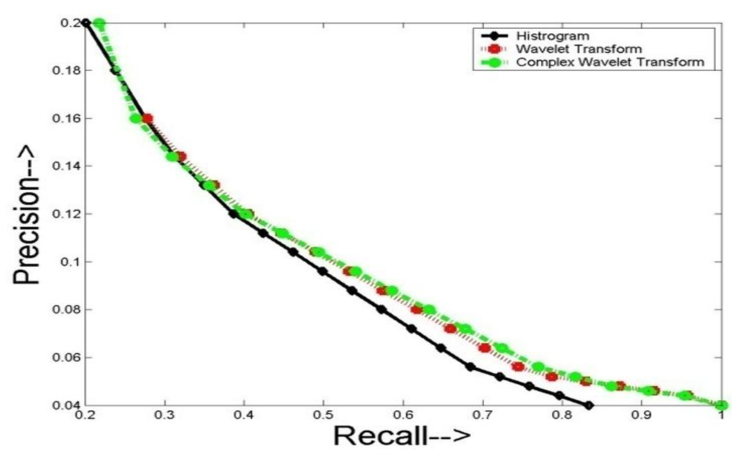

Figure 12 Precision – Recall Curve

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